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COMPARISON OF CONTROLLERS FOR SHIP AUTOPILOTS

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Abstract

Majority of vessels at sea employ traditional Proportional Integral Derivative (PID) controller for manoeuvring. A vast majority of control algorithms are available; however, most designers use old Ziegler-Nichols tuned PID control which was proposed in 1942. Although some of the recent methods have been used in other areas of engineering yet hardly any of them have been utilized for a ship steering. This paper compares the performance of four of the more recent controllers for ship steering. Zeefakkel ferry and Mariner class ship are chosen to test the performance of the given controllers. Ship models are selected such that the performance of controllers may be evaluated for both open loop stable as well as open loop unstable ships. The controllers are tested through simulation studies.

Comparison study shows that Internal Model Controller performs better but it is suitable only for open-loop stable ships. For ships with open-loop instability Astrom method provides better results. Neural Network based controller should have performed best amongst all but it requires relatively large training data at varying speed.

Keywords:

Ship Steering, PID Control, Internal Model Control, Neural Network based Control, Ship Autopilot.

1. INTRODUCTION

The design of ship autopilots has remained challenge for more than a century. Almost all types of control algorithms including the PID [1], Least Squares Gaussian (LQG) [2-4], Pole placement [5], Fuzzy logic [6,7], Neural Networks [8,9], and many more have been investigated.

However, almost all commercial ships and more than 95% of closed-loop industrial processes use the controllers based on conventional PID algorithm. The measured heading of the ship is compared with desired heading and the resultant error is fed as input to the controller. The rudder angle commanded by the controller is then fed to ship steering machine which moves the rudder accordingly, the result of which is ship following its due course. The automatic ship steering is to fulfil two requirements i.e.,

course keeping and course changing. Course changing requires the controllers to change the heading of ship to desired heading in the shortest possible time without any oscillations in heading. This requirement of fast and accurate response is especially useful in crowded areas to avoid collision. The other requirement to be fulfilled by the ship controller is course keeping. This requires that the ship maintain its fixed course with minimum rudder activity and yaw effects as otherwise fuel consumption and wear on propeller blades would rise.

The performance of an automatic ship steering control depends upon type of ship under consideration, environmental conditions, performance criterion (eg. Fast or economical response) among other things. A vast majority of controllers are available. Some of them are better than others. The main purpose of this article is to explore any four best controllers for two types of ships, namely a ferry and Mariner Class Ship.

2. MATHEMATICAL MODEL OF THE SHIP

To derive equations of motion of ship an inertial (earth-fixed) and a body-fixed coordinate systems are chosen to describe the dynamics of motion of a ship. The nomenclature of ships' horizontal motion is described using Fig. 1.

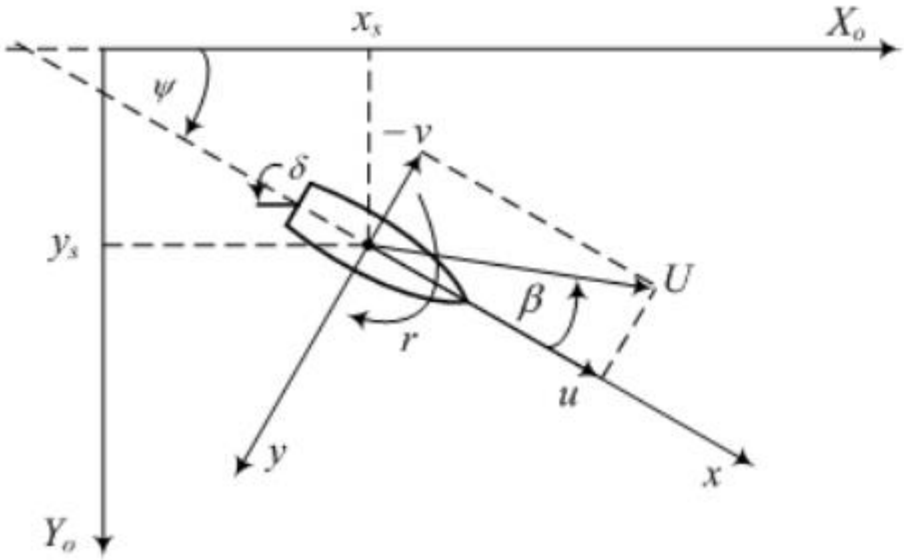

Fig. 1. Variables used to describe the horizontal motion of ship

2.1 Nomoto's Model

According to Nomoto's Second order model the yaw angle is related to rudder angle as [10]

$$\frac{\Psi(s)}{\delta(s)} = \frac{K(T_3 s + 1)}{s(T_1 s + 1)(T_2 s + 1)}$$

The parameters K, T_1,T_2 and T_3 are called "steering quality indices"

A first order approximation can be obtained by setting $T = T_1 + T_2 - T_3$

$$\frac{\Psi(s)}{\delta(s)} = \frac{K}{s(Ts + 1)}$$

In this article two ships are considered namely a Zeefakkel Ferry and Mariner ship. Different model parameters of the two ships are given in Table 1 [10, 11]

Table: Parameters of the ships under consideration

Ship	**Zeefakkel**	**Mariner**
Length	45	161
Speed	5m/s	7.7m/s
K	0.5	-0.187
T	31	-402.83
b	0.016129	-0.000227
a	0.0322	-0.00248

2.2 Effect of Feed Forward Speed

The effect of forward speed U on ship parameters can be eliminated using non-dimensional quantities. If K_o and T_o are the gain and time constant respectively of Nomoto's first order model at speed U_o then

$$K = \left(\frac{U}{U_o}\right) K_o$$

$$T = \left(\frac{U_o}{U}\right) T_o$$

In this article, the ships are tested at a speed of 5m/s.

2.3 Norrbin's Model

Nomoto's model discussed above is a linear model suitable for constant feed forward speed and small rudder angles. Norrbin's proposed model does not make any such assumption and is given as [11]

$$\delta = m\ddot{\Psi} + d_1\dot{\Psi} + d_3\dot{\Psi}^3$$

where $m = \frac{T}{K}, d_1 = \frac{\alpha_1}{K}\ and\ d_3 = \frac{\alpha_3}{K}$

2.4 Steering Machine

The function of steering machine is to move the rudder to desired heading when commanded by control system [10]. A simplified Simulink model is shown in figure. Rudder limiter and rudder rate limiter are in the ranges

$$\delta_{max} = \pm 35^{\circ} \text{ and } \dot{\delta}_{max} = \pm 5^{\circ}$$

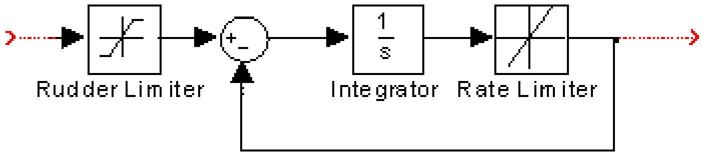

Fig. 2. Ship Steering Machine

3. SHIP COURSE CONTROL

The generalized block diagram of ship steering control system is shown in Fig. 3

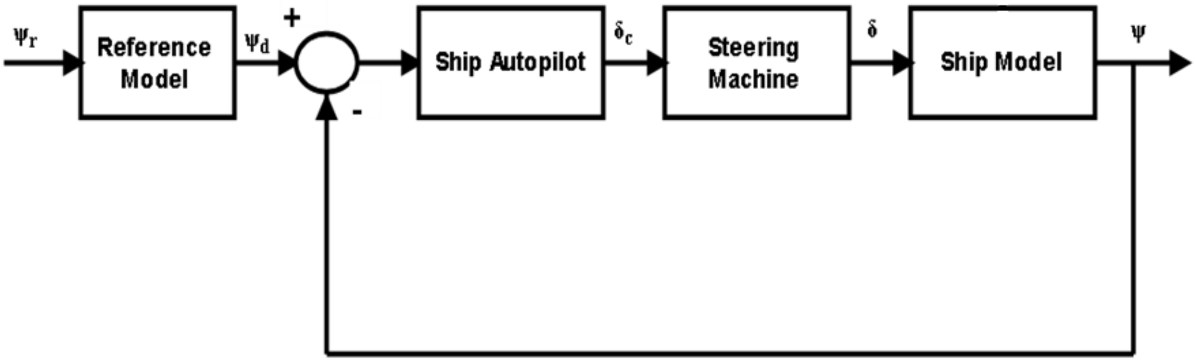

Fig. 3. Block diagram of complete Ship Steering system

In this article, four course changing controllers of the ship are considered

3.1 Fossen Controller

The controller proposed by Fossen [10] relates controller parameters with damping ratio ζ and natural frequency ω_n of a closed loop ship controller

$$K_p = \frac{T\omega_n{}^2}{K} K_d = \frac{2T\zeta\omega_n - 1}{K}$$

$$\frac{K_i}{K_p} \approx \frac{\omega_n}{10} = \frac{\omega_n K_p}{10} = \frac{\omega_n{}^3 T}{10K}$$

3.2 Astrom Controller

Astrom Controller is based on Optimal Control Theory which minimize certain performance index. Stability and maneuverability over a wide operating range, and minimizing propulsion loss due to

rudder movement are the two parameters chosen for the desired performance index expressed as [11]

$$J = \frac{1}{T}\int_0^T (\widetilde{\Psi^2} + \chi\delta^2)dt$$

Then the controller parameters which minimize the above performance index are given as

$$K_p = \begin{Bmatrix} \frac{1}{\sqrt{x}} & b > 0 \\ -\frac{1}{\sqrt{x}} & b < 0 \end{Bmatrix}$$

$$K_d = \begin{Bmatrix} \sqrt{\left(\frac{a}{b}\right)^2 + \frac{2}{b\sqrt{x}}} - \frac{a}{b} & b > 0 \\ -\sqrt{\left(\frac{a}{b}\right)^2 - \frac{2}{b\sqrt{x}}} + \frac{a}{b} & b < 0 \end{Bmatrix}$$

Where $a = \frac{1}{T}$ and $b = \frac{K}{T}$

3.3 Internal Model Controller

The Internal Model Control philosophy relies on the internal model principle, which states: “Accurate control can be achieved only if the control systems encapsulates (either implicitly or explicitly) some representation of the process to be controlled.” The Internal Model Control structure has a controller implementation which includes model of the plant itself.

For a PID controller represented as

$$G_e = K_p\left(1 + \frac{1}{T_i s} + T_d s\right)$$

PID parameters for a wide variety of process models are given in Table 2 [12]

Table 2: PID controller Using Internal Model Controller

Model	Kp	Ti	Td
$\frac{K}{Ts+1}$	$\frac{T}{K\Omega}$	T	---
$\frac{K}{(T_1 s+1)(T_2 s+1)}$	$\frac{T_1+T_2}{K\Omega}$	T1+T2	$\frac{T_1 T_2}{T_1+T_2}$
$\frac{K(-ks+1)}{T^2 s^2+2\zeta Ts+1}$	$\frac{2\zeta T}{K(k+\Omega)}$	$2\zeta T$	$\frac{T}{2\zeta}$
$\frac{K}{s(Ts+1)}$	$\frac{1}{K\Omega}$	---	T

Nomoto's first order model is given by $\frac{K}{s(Ts+1)}$, the PD parameters, as evident from the table above, can be calculated as

$$K_p = \frac{1}{K\Omega}$$

$$K_d = T$$

The integral term is calculated using the rule of thumb

$$K_i = \frac{\omega_n K_p}{10} = \frac{{\omega_n}^3 T}{10K}$$

3.4 Artificial Neural Network

Artificial Neural Networks (ANNs) have been popular choice for control of those problems whose parameters vary with operating conditions. ANNs are universal approximators and mimic the behaviour of the system to any degree of accuracy. In this work, a feedforward ANN has been trained to behave like a PID controller. This a a three layer network which is trained by using the well known error back propagation algorithm. Seven neurons have been used in the hidden layer. Each neuron in the hidden layer uses the tangent hyperbolic function and output neuron uses a linear transfer function. There are three input to the ANN which are the heading error, derivative of heading error and integral of the hidden layer. The only output is the rudder angle. It is possible to use the forward speed as an additional input so that the network can yield robust performance under varying speeds. However, this is a preliminary work in which forward speed has not been taken as an additional input.

4. SIMULATION STUDY

The Fossen controller, Astrom controller, Internal Model Controller and Neural Network Controller described in the article are implemented in Matlab/Simulink. The model is simulated for 100 seconds. The block diagram of the complete ship steering model, shown in figure, is implemented using Simulink.

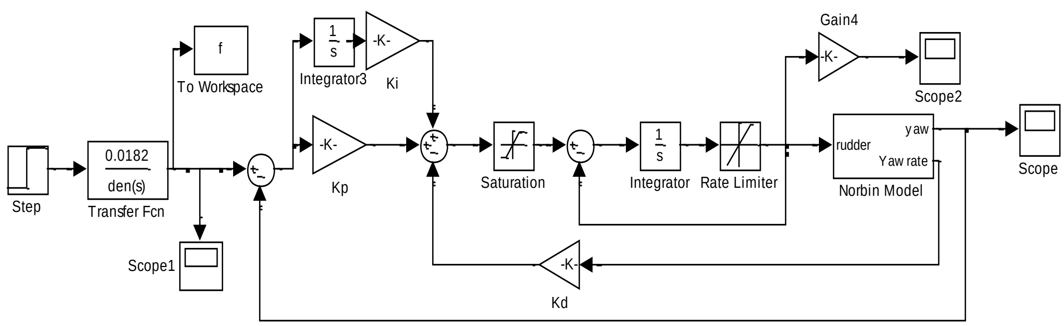

Fig. 5. Actual simulation model implemented in Simulink

The values of controller parameters of different controllers are tuned for best possible results. Natural frequency and damping ratio respectively for Fossen controller are $\omega_n = 0.03$ and $\zeta = 1$ respectively.

$x = 0.08$ for Astrom controller and $\Omega = 0.035$ for Internal Model Controller. Seven neurons are used to create the Neural Network. A step input of 7 degree heading change is given to the model and simulation is run for 100 seconds.

5. RESULTS AND DISCUSSION

In this section, the results of different controllers for ship autopilot are compared. In addition to heading response by different controllers, rudder responses are also compared with each other to check for saturation. Fig. 6 compares the course followed by Zeefakkel Ferry as generated by different controllers and Fig. 8 compares the course followed by Mariner Class ship. Fig. 7 and Fig. 9 compares the rudder response of all four controllers for Zeefakkel Ferry and Mariner Class Ship respectively.

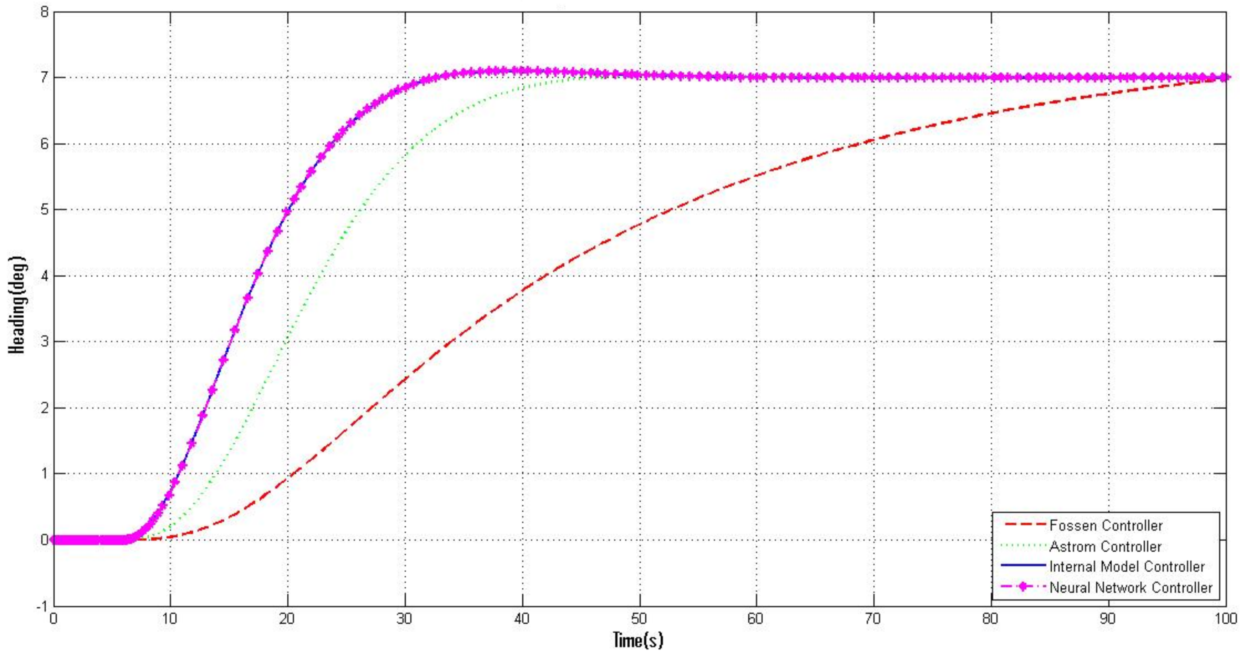

Fig. 6. Comparison of Heading Response for different controllers on Zeefakkel Ferry

During the initial 10 sec in Fig. 6, there is hardly any response by all controllers. This is due to the presence of reference model which smoothes out abrupt step input and provides the input to system gradually. For the next part of the response, as illustrated in Fig. 6 all three controllers except Fossen controller move the Ferry to desired heading of 7 deg in reasonable time. However the Fossen controller takes full 100 seconds to reach the desired heading. If the simulation time is increased it would be found that there is a large overshoot by Fossen controller and it almost takes a 1000 seconds to reach the desired heading.

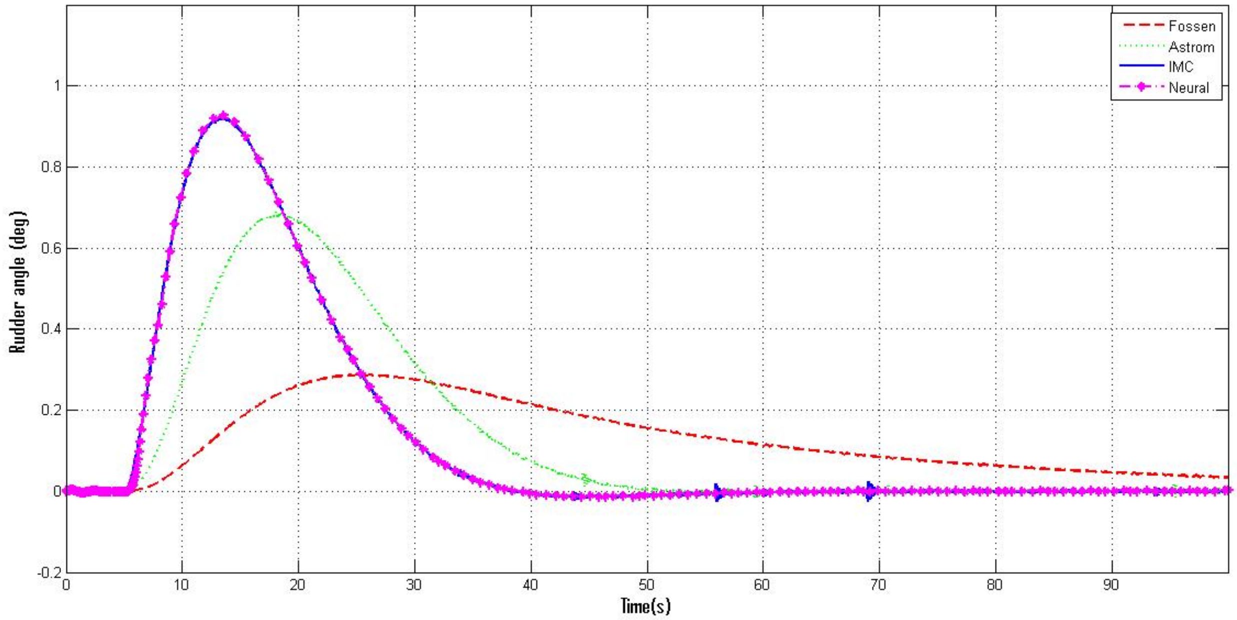

Fig. 7. Comparison of Rudder Response for different controllers on Zeefakkel Ferry

Fig. 7 illustrates the rudder responses by all four controllers. As is evident from Fig. 7 the rudder responses from all the controllers stayed within prescribed limits of saturation. However the rudder response of Fossen controller hardly showed any movement which proves the sluggishness of Fossen controller.

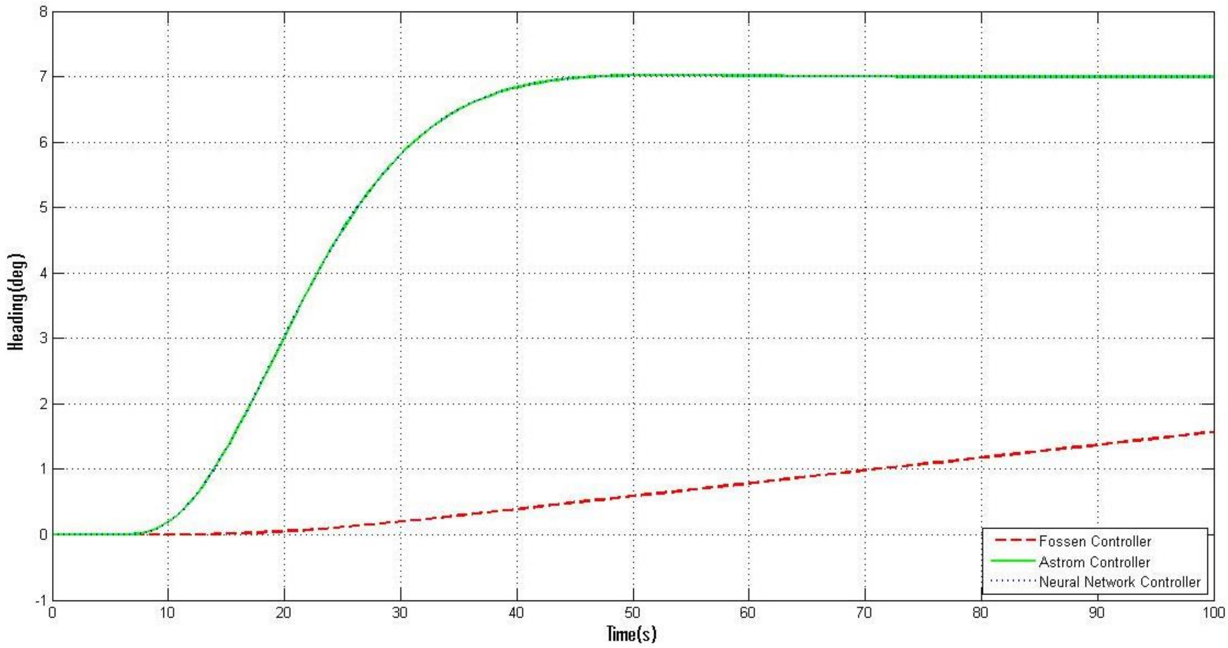

Fig. 8. Comparison of Heading Response for different controllers on Mariner Ship

Fig. 8 compares the heading response of different controllers for Mariner Class Ship. Internal Model Control on Mariner produces dangerously large oscillations and has therefore been neglected from

the comparison. This is due to the fact that IMC is only applicable on those ships which are open loop stable and the Mariner is open-loop unstable. Here again Fossen controller shows extremely sluggish response. Neural Network controller was trained using Astrom controller's data, therefore, their curves coincide.

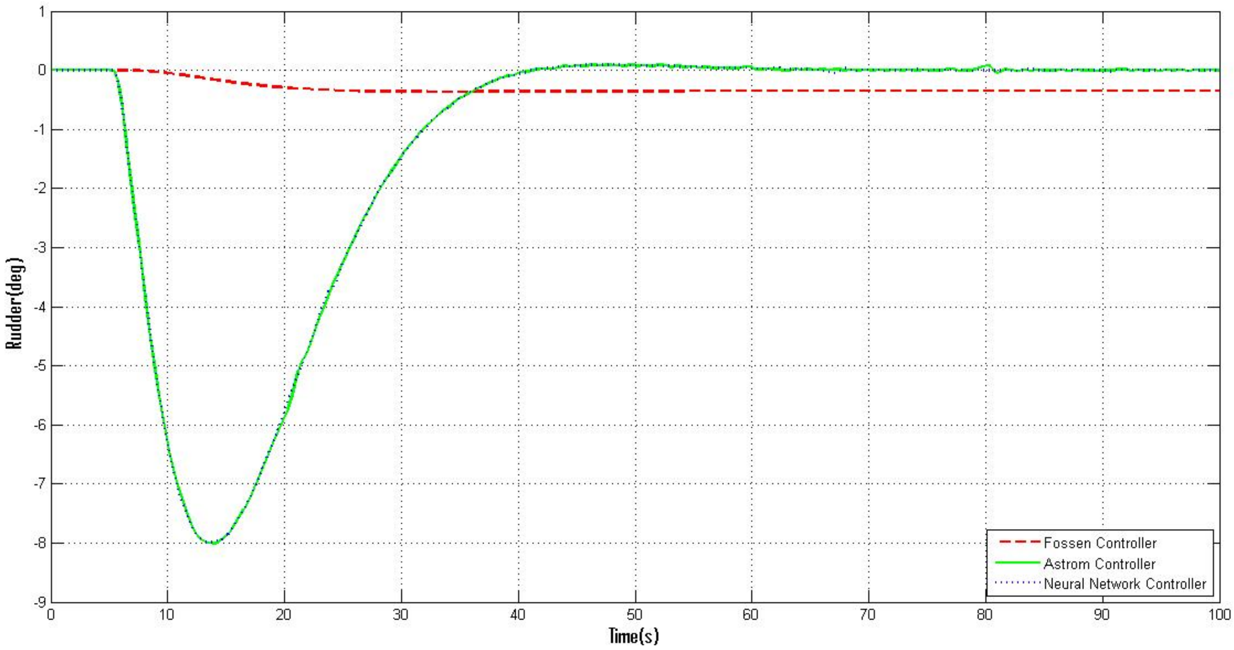

Fig. 9. Comparison of Rudder Response for different controllers on Mariner Ship

6. CONCLUSION

In this study, four types of controllers are used as autopilot for Zeefakkel Ferry and Mariner Class ship and their responses are compared. The complete models are simulated in Matlab/Simulink. Heading and rudder responses are compared against each other. The comparison reveals that Fossen controller performed worst for both the ships as it was very sluggish and had a dangerously large overshoot (not shown in diagram below due to small time range). Astrom controller performed relatively better but it also took longer time to reach steady state for Zeefakkel Ferry. For Mariner Class Ship Astrom controller performed best. Internal model controller and neural network controller trained using data set of IMC performed best in case of Zeefakkel Ferry but for Mariner Ship, IMC was not tested as it only can be used for open-loop stable ships whereas Mariner is open-loop unstable. Neural Network performed good for all cases and will continue to do so provided it has sufficiently large data set to be trained.

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